

Retrospective Analog Year Analyses Using NASA Satellite Data to Improve USDA's World Agricultural Supply and Demand Estimates

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Introduction

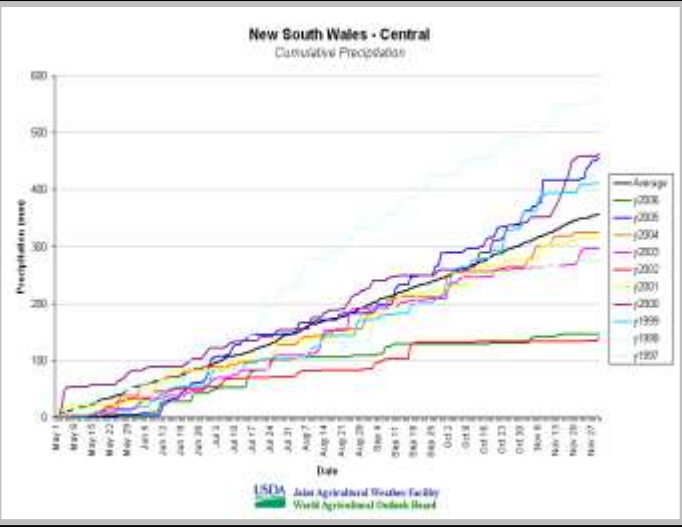
The **USDA World Agricultural Outlook Board (WAOB)** is responsible for monitoring weather and climate impacts on domestic and foreign crop development. One of WAOB's primary goals is to determine the net cumulative effect of weather and climate anomalies on final crop yields. To this end, a broad array of information is consulted, including maps, charts, and time series of recent weather, climate, and crop observations; numerical output from weather and crop models; and reports from the press, USDA attachés, and foreign governments. The resulting agricultural weather assessments are published in the **Weekly Weather and Crop Bulletin**, to keep farmers, policy makers, and commercial agricultural interests informed of weather and climate impacts on agriculture.

Because both the **amount** and **timing** of **precipitation** significantly affect crop yields, WAOB often uses precipitation time series to identify growing seasons with similar weather patterns and help estimate crop yields for the current growing season, based on observed yields in analog years. Historically, these analog years are visually identified; however, the qualitative nature of this method sometimes precludes the definitive identification of the best analog year. Thus, one goal of this study is to derive a more rigorous, statistical approach for identifying analog years, based on a modified coefficient of determination, termed the **analog index (AI)**. A second goal is to compare the performance of AI for time series derived from surface-based observations vs. satellite-based measurements (NASA TRMM and other data). Previous work has shown promise towards achieving these goals (Teng and Shannon, 2010).

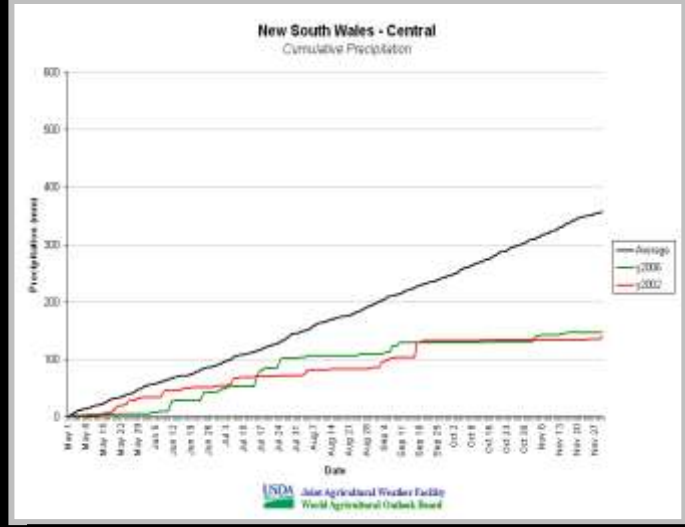
Analog Year Comparisons for Crop Yield Forecasts

An example ...

... between a given year and historical years with similar weather patterns, from New South Wales, Australia.



2006 is the target year...
... what year(s) are similar?



2006 is the target year...
... 2002 is an analog year.

Actual Winter Wheat Yields	
Year	ΔYield from Trend (ton/ha)
2006	-1.83
2005	-0.05
2004	-0.51
2003	-0.42
2002	-1.96
2001	0.15
2000	0.00
1999	0.40
1998	-0.01
1997	-0.03

In 2006, drought in New South Wales threatened a reduction in winter wheat yields estimated by WAOB meteorologists to be similar to that of 2002, based on analog analyses of precipitation time series. Indeed, following the harvest, wheat yields were found to be well below the trend. Although the weather was similar in both years, yields differed. This variability can be attributed to a number of factors, including subtle differences in the timing of the rainfall, varieties of wheat planted, and amount of wheat grazed rather than harvested.

Figure to the right, of Western Australia, illustrates the importance of timing of precipitation relative to the stages of crop development. Similar amounts of rain fell during the 2002 and 2006 winter wheat growing seasons. In 2002, however, a noticeable drying trend occurred as the season progressed. In contrast, in an otherwise dry 2006 growing season, a period of near-normal rainfall during the middle of the season benefited the crop, as it approached the moisture-sensitive reproductive stages of development in early September. This timely rainfall helped to elevate 2006 winter wheat yields (1.27 t/ha) to above 2002 levels (0.91 t/ha).



Method

The coefficient of determination is often used to measure how well modeled estimates represent observed values. A generic form of the coefficient of determination (R^2) can be expressed as

$$R^2 = 1 - \frac{\sum_i (OBS_i - MOD_i)^2}{\sum_i (OBS_i - \overline{OBS})^2}$$

where OBS are observed values, MOD are modeled estimates, and \overline{OBS} is the mean of the observed data. An R^2 of 1.0 indicates that the observed data and modeled estimates are perfectly correlated but does not guarantee that they are identical. Because the generic form of the coefficient of determination is unable to simultaneously resolve similarities in the timing and magnitude of precipitation, a modified form of this equation was used in this study to identify analog years. The modified equation, termed the analog index (AI), is expressed as

$$AI = 1 - \frac{\sum_i (P_i - PA_i)^2}{\sum_i (P_i - coeff * P_i)^2}$$

where P is the precipitation during the target year, PA is the precipitation during the potential analog year, and $coeff$ serves as a threshold that helps evaluate the goodness of fit between P and PA . AI values range from $-\infty$ to 1.0, with values approaching 1.0 indicative of the strongest analog relationships between P and PA . In this study, time series with positive AI values are considered analog years.

Values of $coeff$ could range from 0.0 to 1.0 and, theoretically, be arbitrarily set close to 1.0, to limit the number of time series that qualify as analog years. However, when the same $coeff$ was applied across different areas or different target years, the results were poor, suggesting that a unique $coeff$ is needed for each study area and time period of interest, to identify the best set of analog years. Because the $coeff$ is an unknown for each study area and time period, an iterative approach was adopted for calculating the AI .

In this study, the 2008 growing season was selected as the target year. The 2003, 2004, 2005, 2006, and 2007 growing seasons were treated as potential analog years. Initially, the AI was calculated for each potential analog year using a $coeff$ of 0.95. The AI values were then summed to determine the strength of the analog relationships. If the sum was less than 1.0, no strong analogs were identified, so the $coeff$ was decreased a small amount and the AI values and the sum of these values were recalculated. This iterative process was repeated until the sum of the AI values equaled 1.0 or the $coeff$ equaled 0.0. This approach ensured that only the strongest analog years were identified AND that no analog years were identified if the time series were not reasonably similar to the target year.

Study areas

Five major agricultural regions worldwide were analyzed. The size of individual study areas selected depends on the variability of weather within each area and the availability of crop yield data.



Iowa is the largest corn producing state in the U.S., accounting for about 19% of domestic production annually. U.S. is the largest corn producer and exporter in the world.



Approximately 70 percent of total corn production in Mexico come from eight states. Including Jalisco, Mexico is the fourth largest corn producing country in the world.



Parana historically is one of the largest soybean-producing states in Brazil, which is a major soybean exporter.



Argentina is the world's second largest exporter, and fifth largest producer, of corn.



Free State is the largest corn-producing state in South Africa.

Data Sets

- Station-based precipitation:** Regional time series are derived by averaging daily cumulative precipitation from multiple surface observing stations distributed evenly throughout each study area. **Iowa, U.S. – 8 stations** from NOAA/NWS Cooperative Observer Program (COOP) network; **Jalisco, Mexico – 4 stations** from World Meteorological Organization (WMO) network; **Parana, Brazil – 6 WMO stations**; **central Argentina – 5 WMO stations**; **Free State, South Africa – 5 WMO stations**.
- Crop yield:** U.S. – annual state-level corn statistics from USDA National Agricultural Statistics Service (NASS); Mexico - Secretaría de Agricultura, Ganadería, Desarrollo Rural, Pesca y Alimentación (SAGARPA); Brazil – annual soybean statistics from Instituto Brasileiro de Geografia e Estatística; Argentina - Ministerio de Agricultura, Ganadería y Pesca (MAGyP); South Africa – National Estimates Committee (NEC).
- TRMM Multi-satellite Precipitation Analysis** (TMPA; 3B42-V6) (Huffman et al., 2007): 0.25-deg; daily (averaged from 3-hourly); source data sets merged (TRMM, AMSR-E, SSM/I, others); temporal coverage 1998-present.

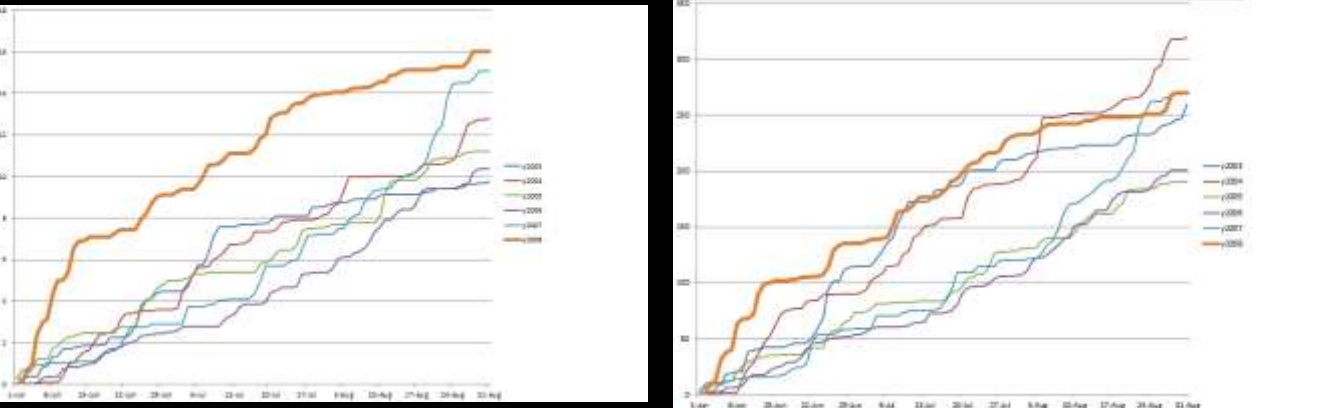
Results

REGION (SFC/SAT)	Coeff	2003 AI (Analog year rank)	2004 AI (Analog year rank)	2005 AI (Analog year rank)	2006 AI (Analog year rank)	2007 AI (Analog year rank)
Iowa, U.S. (SFC)	0.50	0.29 (2)	0.36 (1)	0.23 (3)	0.0 (–)	0.12 (4)
Iowa, U.S. (SAT)	0.78	0.59 (1)	0.42 (2)	0.0 (–)	0.0 (–)	0.0 (–)
Jalisco, Mexico (SFC)	0.73	0.09 (3)	0.22 (2)	0.0 (–)	0.0 (–)	0.69 (1)
Jalisco, Mexico (SAT)	0.66	0.0 (–)	0.08 (3)	0.0 (–)	0.27 (2)	0.65 (1)
Parana, Brazil (SFC)	0.66	0.0 (–)	0.56 (1)	0.05 (3)	0.0 (–)	0.38 (2)
Parana, Brazil (SAT)	0.69	0.0 (–)	0.43 (2)	0.0 (–)	0.0 (–)	0.57 (1)
central Argentina (SFC)	0.73	0.0 (–)	0.48 (2)	0.0 (–)	0.52 (1)	0.0 (–)
central Argentina (SAT)	0.85	0.498 (2)	0.0 (–)	0.0 (–)	0.505 (1)	0.0 (–)
Free State, South Africa (SFC)	0.72	0.53 (1)	0.13 (3)	0.33 (2)	0.02 (4)	0.0 (–)
Free State, South Africa (SAT)	0.8	0.0 (–)	0.0 (–)	0.77 (1)	0.0 (–)	0.23 (2)

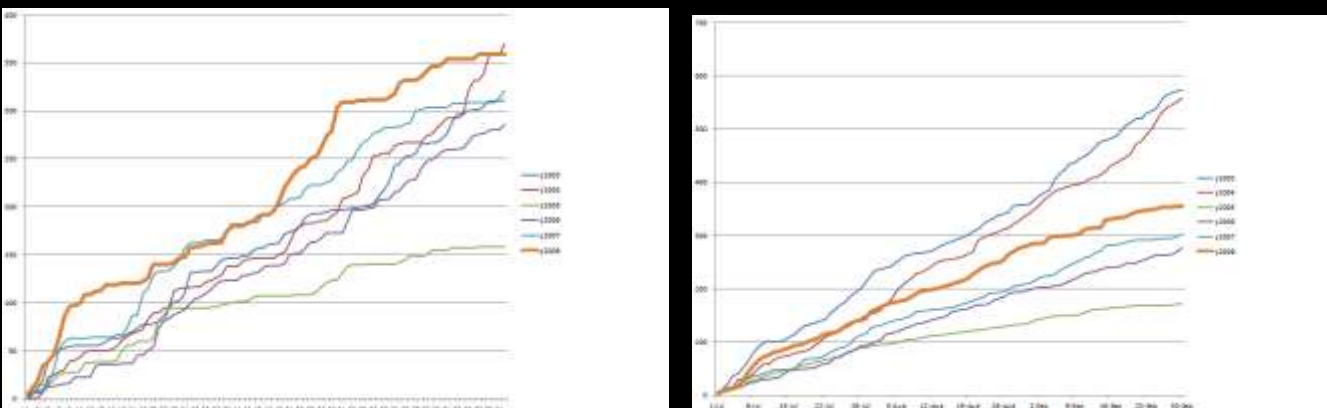
Left figure of each area: WMO station precipitation, except Iowa (COOP station precipitation).

Right figure of each area : TMPA 3B42-V6 precipitation. All precipitation is cumulative.

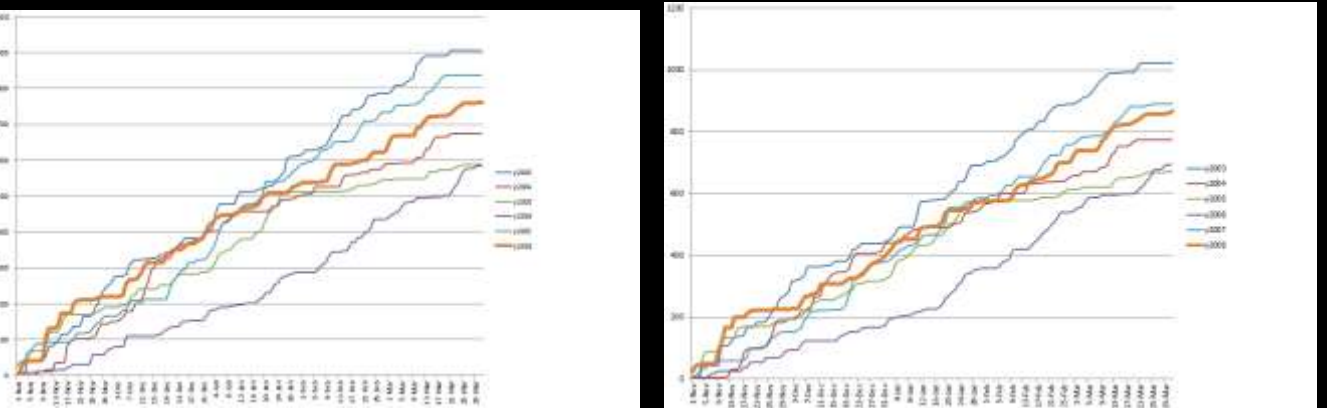
Iowa, U.S. (corn)



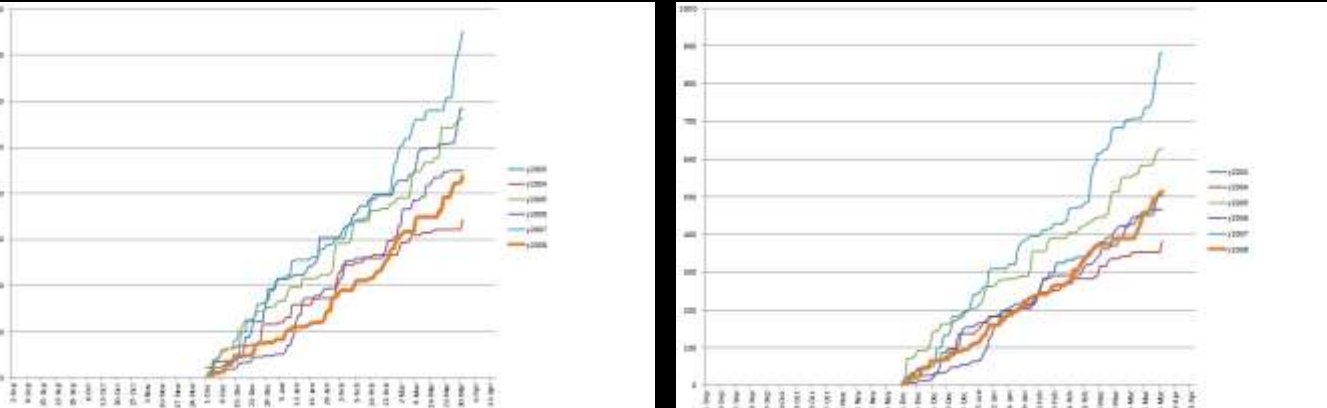
Jalisco, Mexico (corn)



Parana, Brazil (soybeans)

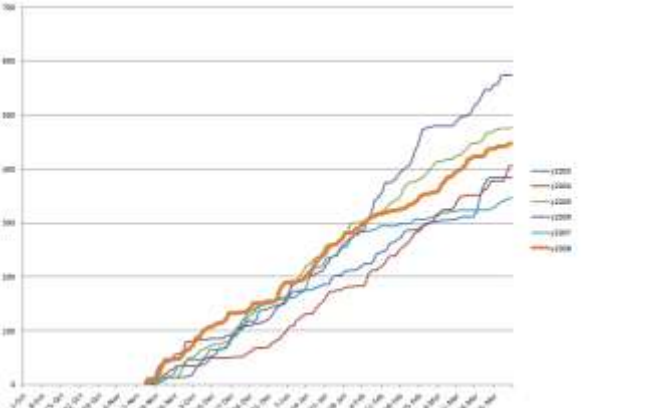
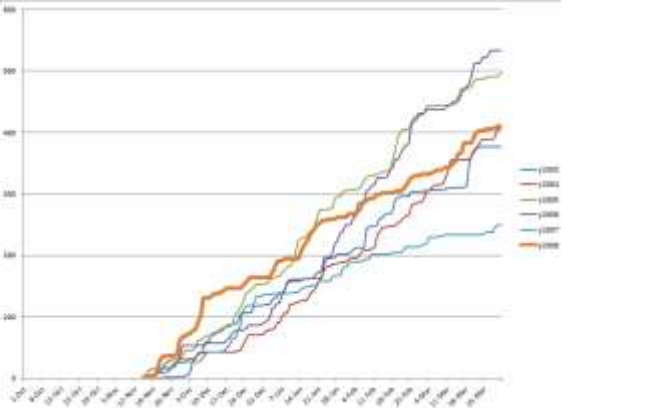


Central Argentina (corn)



Results (cont.)

Free State, South Africa (corn)



REGION (crop)	Measured yield deviations from the 10-yr trend (OBS)	Estimated yield deviations from trend based on surface data (SFC)	Absolute value of OBS-SFC	Estimated yield deviations from trend based on satellite data (SAT)	Absolute value of OBS-SAT
Iowa, U.S.A. (corn)	-0.53 (t/ha)	0.31	0.84	0.26	0.79
Parana, Brazil (soybeans)	0.33 (t/ha)	0.02	0.31	0.12	0.21
central Argentina (corn)	-0.79 (t/ha)	-0.49	0.30	-0.51	0.28
Jalisco, Mexico (corn)	-0.44 (t/ha)	0.05	0.49	-0.07	0.37
Free State, South Africa (corn)	0.53 (t/ha)	0.13	0.40	0.30	0.23

• For all five study areas, the difference between measured deviation from the 10-yr trend (OBS) and estimated deviation based on surface data (SFC) is larger than the difference between OBS and estimated deviation based on satellite data (SAT).

• To test if the traditional, visual method of identifying analog years also improves with the addition of satellite data, a USDA WAOB agricultural meteorologist was provided the same data that this study used and asked to identify the analog year(s) for the 2008 target year.

• For all the study areas thus tested, the analyst selected analog year(s) with better yield estimates, using satellite data.

Discussions and Summary

• Five study areas and six growing seasons of data were analyzed (2003-2007 as potential analog years and 2008 as the target year).

• Results thus far show that, for all five study areas, crop yield estimates derived from satellite-based precipitation data are closer to measured yields than are estimates derived from surface-based precipitation measurements.

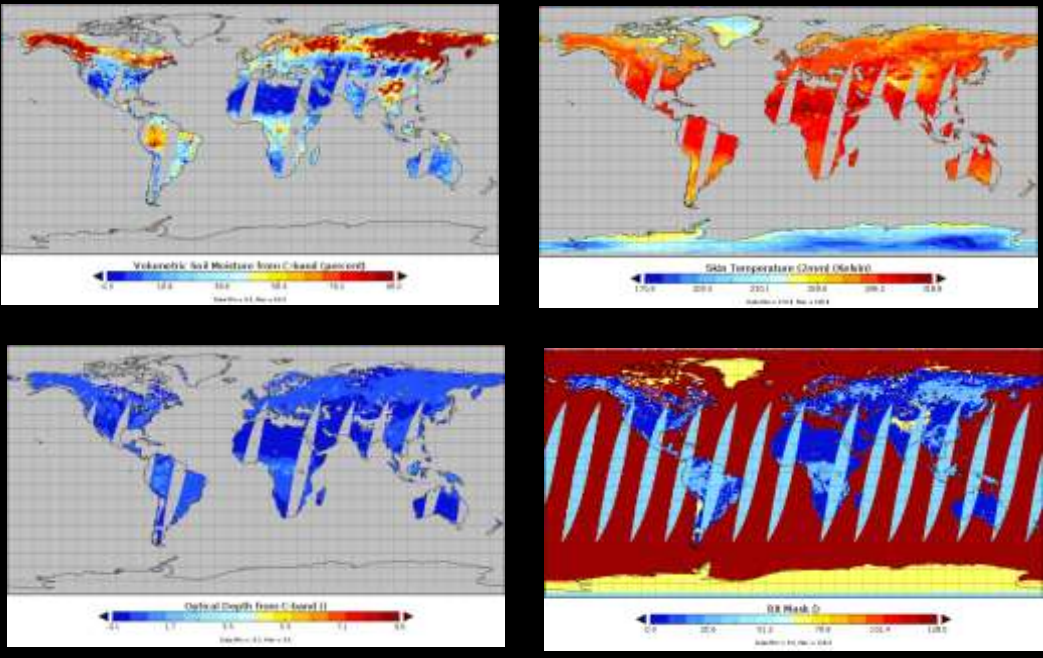
• Satellite data being at least comparable to weather station data, in identifying analog years, points to the possibility of "calibrating" the analog analysis methodology in station-rich areas, to be then applied in station-poor areas of the world, which would significantly extend the global coverage of WAOB analysts in conducting crop yield forecasts.

• Work is continuing to include satellite-based surface soil moisture data and model-assimilated root zone soil moisture.

• This study is part of a larger effort to improve WAOB estimates by integrating NASA remote sensing observations and research results into WAOB's decision-making environment. Use of retrospective analog analysis as a metric for assessing the effect of integrating NASA data into WAOB seems promising.

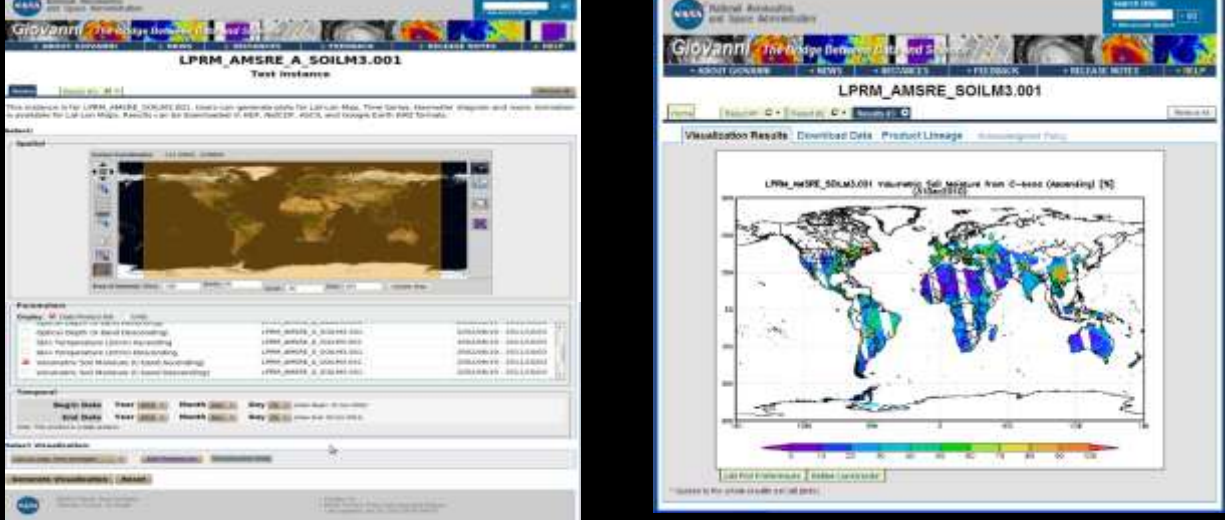
Project Status – What else and what's coming

LPRM L2, L3 production

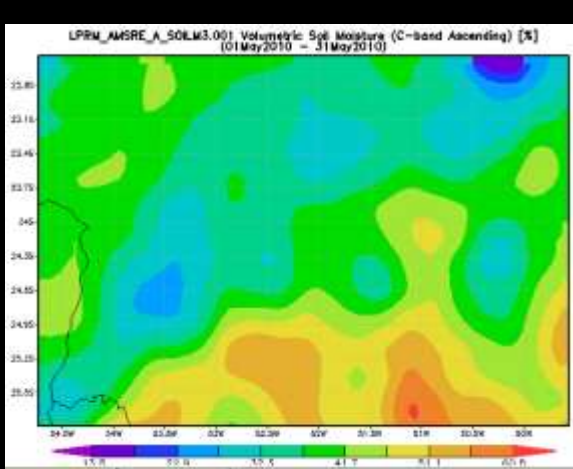


- Provide global soil moisture with high temporal resolution and 0.25 degree spatial resolution, for the top few cm of the soil column (Owe et al., 2008).
- Extensively validated; has an accuracy of $\sim 0.06 \text{ m}^3 \text{ m}^{-3}$ for sparse to moderate vegetated regions (De Jeu et al., 2008).
- Initial version of both products are operationally available.
- Error estimates to be included in next version.
- Current LPRM products are based on AMSR-E; work to replace AMSR-E is ongoing.

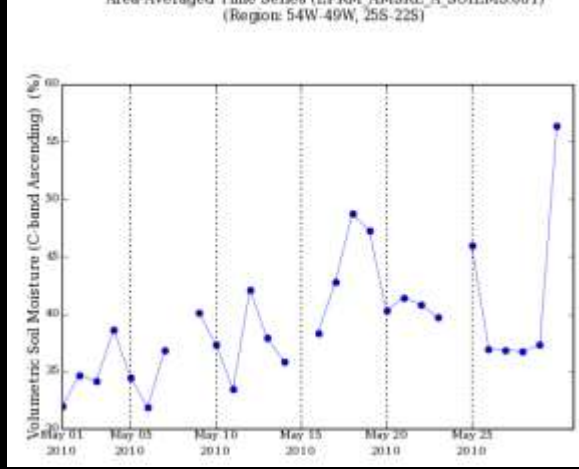
Giovanni-Soil Moisture Portal



Giovanni user interface



Lat-lon map, time-averaged (May 1-31, 2010), Parana, Brazil



Time series (May 1-31, 2010), Parana, Brazil

- Operational release of portal ~early 2012.
- Initial parameters included: LPRM/AMSR-E soil moisture, AMSR-E/Aqua soil moisture, LSMEM/TMI soil moisture, TMPA precipitation, AIRS surface temperature.

References

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- Huffman et al., 2007, The TRMM Multi-satellite Precipitation Analysis: Quasi-global, multi-year, combined-sensor precipitation estimates at fine scale. *J. Hydrometeor.*, 8(1), 38-55.
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